

# Image Fusion Using Cokriging

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## I. INTRODUCTION

Scientists in various disciplines are faced with huge amounts of data that need to be studied and analyzed. NASA alone has approximately 18 satellites with over 80 sensors, all of which continuously collect a tremendous amount of data from around the globe. An important step in modern data processing applications where data are gathered from multiple sources is *data fusion*. Data fusion is defined as the process of dealing with information from multiple sources to achieve refined and improved information for decision making [1]. Image fusion is a subset of the general data fusion problem where data being fused are images. The goal of performing image fusion is usually to increase either the spatial or spectral resolution of images involved.

One particular case of image fusion is *pan-sharpening*. Pan-sharpening is a technique which deals with the limitations of sensors in capturing high resolution multispectral (MS) images [2]. Panchromatic (Pan) images have high spatial resolution and low spectral resolution. On the other hand, MS images have high spectral resolution, since they cover a narrower wavelength range, but have a lower spatial resolution. Image fusion is then used as a tool to create a high spatial and spectral resolution image given Pan and MS images. In this paper we show how to apply fusion for the purpose of pan-sharpening multispectral Landsat ETM bands by using cokriging.

We employ the *cokriging* interpolation method for image fusion of remotely sensed data [3], [4]. In particular, we show preliminary results on applying a variant called *ordinary cokriging* for pan-sharpening of multispectral images from the Landsat 7 sensor. We initially proposed cokriging for image fusion in [5] and showed preliminary results on increasing the spectral resolution of ALI using Hyperion. In this paper, we address the problem of increasing the spatial resolution of multispectral bands of a sensor using a panchromatic image. We then evaluate both spectral and spatial quality of our fused images through a few quantitative measures. We also compare our results to those obtained from more traditional approaches based on principal component analysis and wavelets.

## II. ORDINARY COKRIGING FOR DATA FUSION

Kriging is an interpolation method named after Danie Krige, a South African mining engineer, who pioneered in the field of geostatistics [3]. There are variants of this interpolation method. The most commonly used variant is called *ordinary kriging*, which is often referred to as a *best linear unbiased*

*estimator*. It is considered to be *best* because it aims to minimize variance of the estimation error. It is *linear* because estimates are weighted linear combination of known values, and is *unbiased* since it constrains the mean error to be equal to zero [4]. Kriging and its variants have been traditionally used in mining and geostatistics applications [3], [4], [6]. Kriging is also referred to as the *Gaussian process predictor* in the machine learning domain [7].

We find cokriging suitable for various applications of data fusion for the following reasons:

- Ordinary cokriging is a *best* unbiased linear estimator.
- Cokriging can integrate data of various natures.
- Cokriging can interpolate arbitrary scattered data. Unlike many other image fusion methods, cokriging does not require resampling of the data sets when registration of the remotely sensed data is being performed. This avoids introduction of errors due to rotation, translation, and interpolation of the data during the resampling process.
- Cokriging is applicable to the vision of future sensor networks, where many small sensors are located at scattered locations. Using cokriging one can estimate sensor measurements for a particular property at locations where those values are missing.

In this paper, we explore using cokriging for pan-sharpening or improving the spatial resolution of multi-spectral imagery.

## III. DATA SETS

We used Landsat 7 ETM data sets provided by the IEEE Data Fusion Committee, data set grss.dfc.0002 [8]. The images were taken over Hasselt (Belgium) in 1999. Landsat 7 ETM imagery has 8 bands. Landsat data specifications are presented in Table I. Note that the spectral resolution of the panchromatic band 8 corresponds to MS bands 2, 3, and 4 combined. Thus, for our experiments, we used a  $200 \times 200$  subset of multispectral bands 2, 3, and 4 and their corresponding  $400 \times 400$  panchromatic band 8 which are shown in Figures 1 and 2 respectively.

## IV. METHODS

We performed pan-sharpening of Landsat MS bands 2, 3, and 4 by fusing them with Pan band 8 using three different fusion methods: cokriging, principal component analysis (PCA), and wavelet-based fusion. In this section, we describe each method briefly.

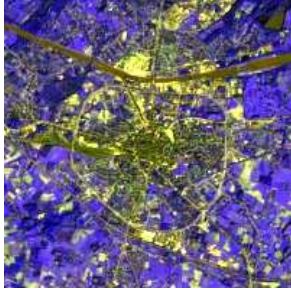


Fig. 1. Landsat 7 Multispectral Bands 2, 3, and 4. Landsat 7 image courtesy ESA 1999 - distribution Eurimage.

TABLE I  
LANDSAT 7 ETM DATA SPECIFICATION

Band	Resolution	
	Spatial (meters)	Spectral ( $\mu m$ )
1	30	0.45–0.52
2	30	0.53–0.61
3	30	0.63–0.69
4	30	0.78–0.90
5	30	1.55–1.75
6	30	10.4–12.5
7	30	2.09–2.35
8	15	0.52–0.90

#### A. Cokriging

By linearity, the interpolated estimate  $H$  produced by cokriging at some location  $0$  is a linear combination of variables of interest. In our case we have two types of variables: high spatial resolution data and high spectral resolution data. We represent these two types of variables by  $h$  and  $l$  respectively, and we represent random functions generating these variables by  $H$  and  $L$ .

The estimate of  $H$  at location  $0$ ,  $\hat{h}_0$ , using the two sets of variables as mentioned in [4], is given by  $\hat{h}_0 = \sum_{i=1}^n a_i h_i + \sum_{j=1}^m b_j l_j$ , where  $h_1, h_2, \dots, h_n$  are primary data (high spatial resolution data in our application) at  $n$  nearby locations,  $l_1, l_2, \dots, l_m$  are secondary data (high spectral resolution data for our case) at  $m$  nearby locations, and  $a_1, a_2, \dots, a_n$  and  $b_1, b_2, \dots, b_m$  are cokriging weights which will be calculated. The estimation error,  $R$ , is calculated as  $R = \hat{h}_0 - h_0 = w^t Z$ , where  $w^t = (a_1, \dots, a_n, b_1, \dots, b_m, -1)$ , and  $Z^t = (h_1, \dots, h_n, l_1, \dots, l_m, h_0)$ . The goal of cokriging is to find the weight vector  $w^t$  such that the variance of the error is minimized and the estimate for  $\hat{h}_0$  be *unbiased*, that is, the mean error residual is zero.

There are various types of the cokriging methods. Here we illustrate the *ordinary cokriging*. Ordinary cokriging requires that  $\sum_{i=1}^n a_i = 1$  and  $\sum_{j=1}^m b_j = 0$ . These two constraints make our estimate unbiased (see [4] for details). So now we have an optimization problem with two constraints. Let  $C_z$  represent pairwise covariances of variables in vector  $Z$ . Then, using Lagrange multipliers  $\mu_1$  and  $\mu_2$ , the objective function of our optimization problem is as follows.

$$\text{Var}(R) = w^t C_z w + 2\mu_1 \left( \sum_{i=1}^n a_i - 1 \right) + 2\mu_2 \left( \sum_{j=1}^m b_j \right).$$



Fig. 2. Landsat Panchromatic Band 8. Landsat 7 image courtesy ESA 1999 - distribution Eurimage.

Once the above system of equations is solved, we have the desired coefficients  $a_1, a_2, \dots, a_n, b_1, b_2, \dots, b_m$  to estimate function  $H$  at location  $0$ .

In order to set up the linear system, one needs to model pairwise covariances among available measurements. A requirement on these models is that they should generate a positive definite covariance matrix. A few covariance models are known to have this property (see [3], [4] for more details). We selected a few of these models with a limited number of parameters, and in each case we chose the one which best fit our data, which was spherical model with range 10. We performed our modelling and cokriging interpolation through a freely available software for interpolation of agro-climatic data [9]. For each query point, we considered its 32 nearest neighbors although different neighborhood sizes may result in better results. Cokriging interpolation and evaluation steps are computationally expensive tasks. For this reason, and because far points are expected to have less effect on interpolation weights, cokriging systems are traditionally solved over a local neighborhood from the query point [3], [4]. Efficient implementations of these tasks will be the focus of our future research. Pan-sharpened MS bands 2, 3, and 4 (fused bands) by cokriging are shown in Figure 3.

#### B. Principal Component Analysis (PCA)

We applied PCA for image fusion similarly to [10], [11]. First, we performed principal component transformation on Landsat multispectral bands. Then, the first principal component (PC) was replaced with the high resolution Pan band, which was scaled so that its mean and standard deviation match those of the first principal component of the MS bands. This scaling was performed to avoid distortion of the spectral information. Then, the first component was replaced by the

stretched band. We then proceeded by performing inverse PCA on the stretched pan band and other PCs.

### C. Wavelet-Based Fusion

A wavelet decomposition of any given signal (1-D or 2-D) is the process that provides a complete representation of the signal according to a well-chosen division of the time-frequency (1-D) or space-frequency (2-D) plane [12]. Through iterative filtering by low-pass and high-pass filters, it provides information about low- and high-frequencies of the signal at successive spatial scales. For fusion purposes, multi-resolution wavelet decomposition separates high- and low-frequency components of the two given data sets and these components are then recomposed differently in the reconstruction phase.

In our experiments, we are using a Daubechies filter [12] of size 4 and a Mallat Multi-Resolution Analysis (MRA) [13] decomposition and reconstruction scheme. Then, components from both decompositions are combined during the reconstruction phase to create the new fused data. In this scheme and similarly to [14], where different spatial resolution data are fused, we fuse the different spectral resolution data in the following manner: high-frequency information of the high spatial resolution data (e.g., Pan Landsat band 8) is combined with low-frequency information of the high spectral resolution data (e.g., Landsat MS bands). In our experiments, the same Daubechies filter of size 4 is used for both decomposition and reconstruction phases and for both types of data.

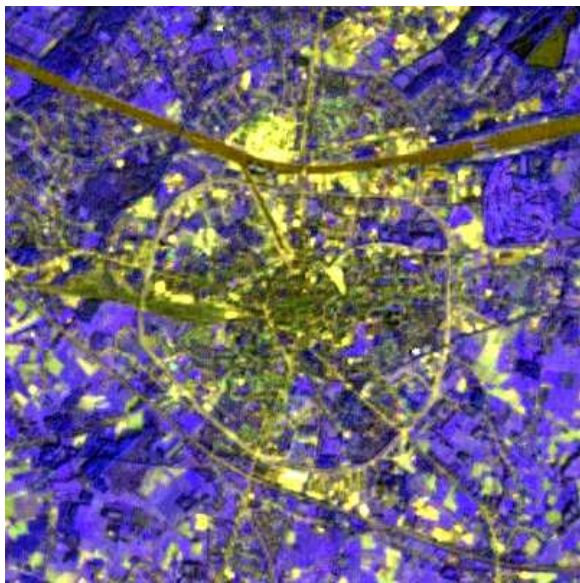


Fig. 3. Landsat Pan-sharpened MS bands 2, 3, and 4 through cokriging with Pan band 8

## V. EVALUATION

We increased the spatial resolution of Landsat ETM multispectral bands 2,3, and 4 by fusing them with its panchromatic band 8. We performed fusion based on cokriging, PCA, and wavelets as described in the previous section. Next, we evaluated the quality of our results. Ideally, this evaluation would

involve a comparison of the classification accuracy on ground-truth data. One could perform classification on input bands and fused bands respectively, assess the classification accuracy through ground truth in each case, and see which fused bands resulted in the most improvement of the classification accuracy. For the area corresponding to the images used in this paper, ground truth is available for SPOT imagery before being registered to the Landsat image. We hope to have the ground truth provided for the SPOT data after it is registered to the Landsat image, and evaluate and report the classification accuracy of the fused images at the conference. For now, we evaluate our fusion methods through a few quantitative methods.

We evaluate both the spectral and spatial quality of our fused bands. The spectral quality was evaluated by calculating how highly each fused band is correlated with its corresponding input MS band. We expect the spectral quality of MS bands to be preserved in the fused bands. Thus, the higher the correlation of the fused bands with their corresponding MS bands is, the better the spectral quality of the fusion.

In order to evaluate the spatial quality of the fused bands we calculate the entropy of the multispectral input bands and their corresponding fused bands. The idea is that the fused images should have enhanced information content compared to their corresponding input MS bands. Thus, the higher the entropy of the fused band is compared to its corresponding MS input band, the better the spatial quality of the fusion is.

In [5] we proposed using Haralick's texture quality metrics [15] as a fusion quality metric. The motivation for doing so is that an image with high textural information is more likely to result in better classification accuracy. Haralick [15] first proposed using a *co-occurrence matrix* to calculate various statistical texture properties for an image. A co-occurrence matrix calculates the number of occurrences of all pairs of gray level which are separated by a distance  $d$  along a given direction. From the co-occurrence matrix, several texture measurements can be computed among which are contrast, variance, and entropy. Usually co-occurrence matrices are calculated locally by considering a small window around each pixel. For each window, co-occurrence matrices are calculated along four directions. Then, a statistical measure (e.g. contrast, variance, entropy) is calculated for that local window. Then, the middle pixel of that window is replaced by the mean of the calculated statistical measure over all four directions. This is repeated for every pixel so that at the end of the process we have an image where each of its pixels is representing a statistical measure of its local neighborhood. We calculated entropy images and then calculated the mean value of each of these images. Increase in mean of entropy images indicates increase in textural information contained in the image, which most likely causes better classification accuracy. However, the true evaluation criteria for our fusion methods would be through ground truth and comparing the classification results of original and fused bands against them.

## VI. RESULTS

First we discuss the spectral quality of fused images using different methods. Pairwise correlation of fused bands and their corresponding input MS bands are shown in Table II. While PCA gives the best spectral quality results for bands 2 and 3, wavelet-based fusion performs best for band 4. However, we see that cokriging performs consistently for all bands and correlations of fused bands with all input MS bands exceeded 90% in all cases. As for spatial quality measures

TABLE II  
CORRELATION OF FUSED BANDS WITH MS INPUT BANDS

Bands	Wavelet	PCA	Cokriging
$f_2, b_2$	0.82	0.99	0.91
$f_3, b_3$	0.84	0.99	0.93
$f_4, b_4$	0.92	0.75	0.93
Average	0.86	0.91	0.92

we considered both the overall entropy of images as well as the mean of entropy images calculated through local co-occurrence matrices [15]. Entropy of input MS bands and fused images are reported in Table III, and the mean entropy of entropy images calculated through local co-occurrence matrices are presented in Table IV. In both cases, cokriging results in increased spatial information compared to their corresponding MS bands. In all cases, cokriging performed better than wavelet-based fusion in increasing the spatial content of MS bands. PCA performed better in spatial domain for bands 3 and 4. However, cokriging performed more consistently overall in increasing spatial information of all MS bands. As we see in Table III, cokriging resulted in higher average entropy of the fused bands compared to PCA and wavelet based fusion. Similarly, results in Table IV indicate that PCA does not increase the textural information significantly for band 2. Cokriging performs more consistently in increasing the textural information across all bands. However, the overall textural information gained are comparable to that obtained from PCA.

TABLE III  
ENTROPY OF MS AND FUSED BANDS

Original Bands		Fused Bands	Wavelet	PCA	Cokriging
$b_2$	2.68	$f_2$	3.12	2.69	3.23
$b_3$	3.01	$f_3$	3.28	3.72	3.64
$b_4$	3.44	$f_4$	3.93	5.21	4.90
Average	3.04		3.44	3.87	3.92

## VII. CONCLUSION

Our experiments indicate that cokriging can be used as a fusion method for pan-sharpening of multispectral data. Methods like PCA or wavelet-based fusion are sensitive to particular wavelengths for preserving spectral resolution of MS bands or increasing their spatial information. Cokriging, on the other hand, performed consistently by producing fused bands that are more than 90% correlated with their corresponding

TABLE IV  
MEAN ENTROPY OF ENTROPY IMAGES OBTAINED THROUGH CO-OCCURRENCE MATRICES

Original Bands		Fused Bands	Wavelet	PCA	Cokriging
$b_2$	1.37	$f_2$	1.37	1.37	1.44
$b_3$	1.42	$f_3$	1.45	1.49	1.45
$b_4$	1.77	$f_4$	1.78	2.02	1.96
Average	1.52		1.53	1.63	1.62

MS input bands and that have significantly increased spatial information compared to their input MS bands. This effort only provides preliminary results on the applicability of cokriging to image fusion. There are various factors and parameters that can lead to better-quality fused images. These include having better models for pairwise covariances of data, and considering the best possible neighborhood size for interpolation of data. Evaluation of the results would also be more accurate if ground truth data were available. These issues along with efficient implementations of cokriging are the focus of our future work.

## VIII. ACKNOWLEDGMENTS

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## REFERENCES

- [1] D. L. Hall, *Mathematical techniques in multisensor data fusion*. Norwood: Artech House Inc, 1992.
- [2] Y. Zhang, "Understanding image fusion," *Photogrammetric Engineering and Remote Sensing*, pp. 657–661, June 2004.
- [3] P. Goovaerts, *Geostatistics for Natural Resources Evaluation*. Oxford: Oxford University Press, 1997.
- [4] E. H. Isaaks and R. M. Srivastava, *An Introduction to Applied Geostatistics*. Oxford: Oxford University Press, 1989.
- [5] N. Memarsadeghi, J. L. Moigne, D. M. Mount, and J. Morisette, "A new approach to image fusion based on cokriging," in *Proceedings of the Eight International Conference on Information Fusion*, vol. 1, Philadelphia, PA, July 2005, pp. 622–629.
- [6] A. Journel and C. J. Huijbregts, *Mining Geostatistics*. New York: Academic Press Inc, 1978.
- [7] C. E. Rasmussen and C. K. I. Williams, *Gaussian Processes for Machine Learning*. MIT Press, 2006.
- [8] "Data fusion community," <http://www.dfc-grss.org>.
- [9] P. Bogaert, P. Mahau, and F. Beckers, "Cokriging software: The spatial interpolation of agro-climatic data," <http://metart.fao.org/T-I/GBR/Tools/Geokrig/Man0.htm>.
- [10] P. S. Chavez, S. C. Sides, and J. A. Anderson, "Comparison of three different methods to merge multiresolution and multispectral data: Landsat TM and SPOT panchromatic," *Photogrammetric Engineering and Remote Sensing*, vol. 57, no. 3, pp. 295–303, March 1991.
- [11] R. Welch and W. Ahlers, "Merging multiresolution SPOT HRV and Landsat TM data," *Photogrammetric Engineering & Remote Sensing*, vol. 53, no. 3, pp. 301–303, 1987.
- [12] I. Daubechies, *10 Lectures on Wavelets*, ser. CMBS-NSF Series Applications in Mathematics. Philadelphia, PA: Society for Industrial and Applied Mathematics (SIAM), 1992.
- [13] S. Mallat, "Theory for multiresolution signal decomposition," *IEEE Pattern Analysis and Machine Intelligence (PAMI)*, vol. 11, no. 7, 1989.
- [14] R. L. King and J. Wang, "A wavelet based algorithm for pan sharpening Landsat 7 imagery," in *International Geoscience and Remote Sensing Symposium (IGARSS)*, vol. 2, 2001, pp. 849–851.
- [15] R. M. Haralick, K. Shanmugan, and I. Dinstein, "Textural features for image classification," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 3, no. 6, pp. 610–621, 1973.